



Disparities in U.S. Economic Network Formation: Gender, Race, and Community Income

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Economic networks provide key opportunities for career progression. We evaluate U.S. LinkedIn network data to examine disparities in network size and growth by gender, race, and local median income. We find large disparities in total network size, but smaller and at times reversed gaps for network growth rates, many of which are narrowing over time. We also demonstrate several important gaps in the inputs to network growth, with members living in lower income communities, Black and Latino members, and women tending to receive fewer invitation requests to connect and many of these same groups having a somewhat lower percentage of invitations they send out being accepted.

Introduction

Our networks play a vital role in connecting us to people, information, and various opportunities. A robust and large network can significantly benefit individuals throughout their careers. In this paper, we delve into the examination of the size and growth of economic networks in the United States, specifically focusing on the number of connections within the LinkedIn platform. While it is important to recognize that the significance of one's network extends beyond mere size and growth rates, analyzing these factors offers valuable insights into one aspect of network strength (Bourdieu, 1986; Zhao, 2002). Essentially, each additional connection in an individual's network presents an additional avenue for information sharing (Aral, 2016) and the establishment of crucial second-degree connections (Granovetter, 1973; Rajkumar et al., 2022).

When presenting the results pertaining to network size or network growth rate, we will provide average values for different populations within the United States. However, we will present these group averages divided by the national average for the same metric, the result of which we refer to as the relative average. There are two primary reasons for adopting this approach. First, it allows us to protect proprietary information regarding LinkedIn membership, as we refrain from reporting actual average network sizes and

growth rates. Second, the relative average serves as an intuitive metric. Consider the example of total network size. A relative average value of one indicates that the subpopulation has, on average, the same network size as the overall national average. A value exceeding one suggests that the subgroup, on average, possesses larger network sizes than the national average, indicating the extent of this difference. For instance, a relative average of 1.2 signifies that the subgroup's average total network size is 20% larger than the national average. Conversely, a relative average of 0.9 indicates that the subgroup has a smaller network size than the national average, specifically 10% smaller.

In our study, we explore network size and growth averages across several key dimensions, namely gender, race, and ZIP Code median income. It is important to acknowledge that gender exists on a spectrum; however, for the purpose of this analysis, we consider gender as a binary classification, distinguishing between men and women. Regarding race, we focus on four racial/ethnic groups: Asian, Black, Latino, and White members among those who have chosen to self-identify their race and ethnicity—hereafter referred to as the Self-ID population.¹ These groups have enough members that we can conduct meaningful analyses.

The inclusion of ZIP Code median income is particularly relevant for this topic, as networks are often established within local contexts. Analyzing

¹ Self-ID refers to a LinkedIn settings option wherein members can opt to privately self-identify their demographic information, including race and ethnicity. When evaluating gender and ZIP Code median income, which is available for virtually all of the U.S. LinkedIn membership, we use the U.S. national average for the relative average denominator. When evaluating race/ethnicity and race/ethnicity by gender, we use the U.S. average across all members who have opted to Self-ID. The reason for this is to provide a fair benchmark comparison in each case, as members who Self-ID tend to be more active and to have larger networks on average, but we are interested in relative averages to the relevant population benchmark.

socio-economic disparities based on locality enables us to investigate potential disadvantages faced by workers residing in lower-income communities compared to their counterparts in higher-income communities. We determine the median income corresponding to the participants' ZIP Code using the American Community Survey. Subsequently, we categorize their ZIP Codes into quartiles based on the median income. The first quartile, or the lowest quartile, represents members residing in ZIP Codes at or below the 25th percentile of median income, indicating lower-income communities. Conversely, the fourth quartile (75th percentile or higher) encompasses members from higher-income communities, with the second and third quartiles following similar definitions. It is also important to note that, while other dimensions such as race may be correlated with ZIP Code median income, the overlap is not perfect and thus offers unique insights into network gaps.

There are a number of important considerations to remember when viewing these results. Observed differences may reflect true differences related to their experiences and decisions, but they may also reflect confounders, especially such factors as how active typical members in a group are on LinkedIn or in which industries they work. Additionally, by limiting the findings to self-identified members for the race/ethnicity findings, the results may not be generalizable to the entire US LinkedIn membership. And the entire US LinkedIn membership may not be representative of the overall U.S. population. This may be particularly true for the industries and occupations in which members work, with LinkedIn being overrepresented in certain professional fields such as engineering. Insofar as

these correlate with some of our examined data dimensions—in particular, ZIP Code median income, but also potentially race/ethnicity and gender—differences between groups may at least partially reflect differences in LinkedIn membership concentration between occupations and industries. Despite these limitations, our analysis can still provide valuable insights into how network trends influence economic opportunities.

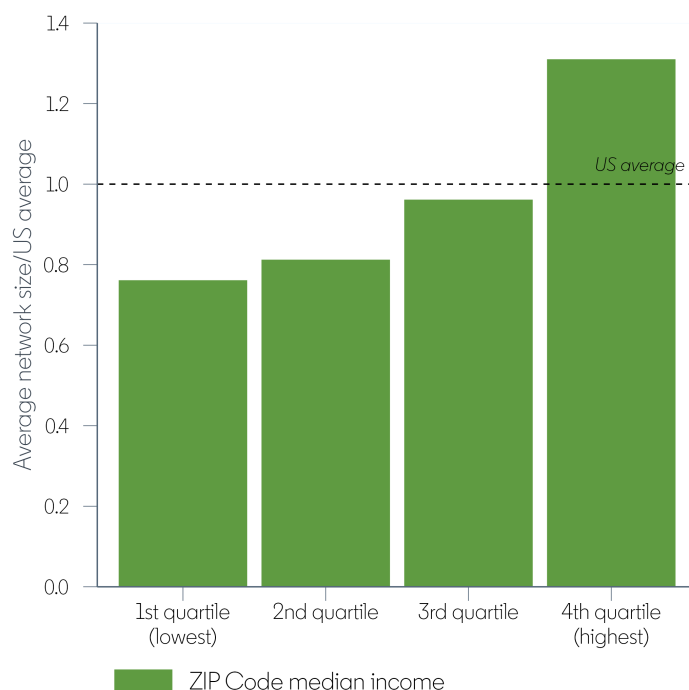
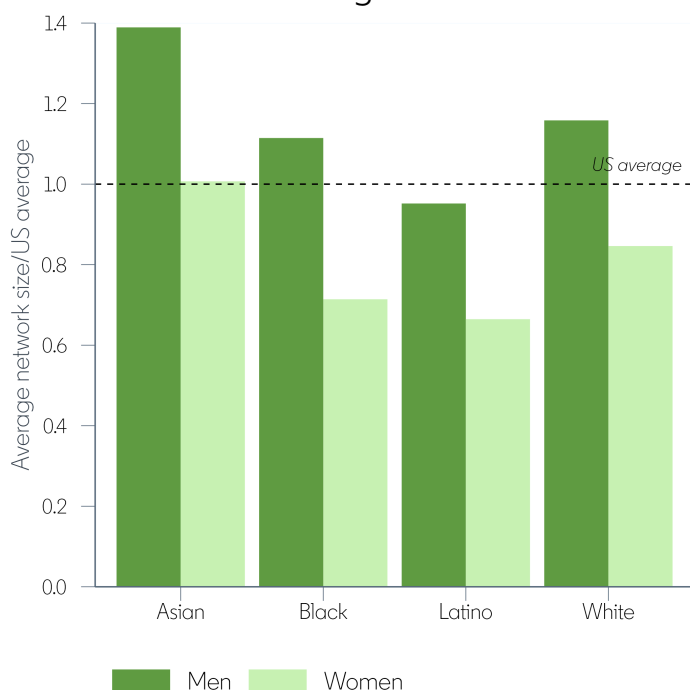
Furthermore, it is important to note that the identification of disparities in network size between different groups does not imply bias within the platform itself. Rather, these disparities are likely to stem from existing inequalities within the labor market and variations in experiences among different groups. It is worth considering that we cannot directly observe the "counterfactual" scenario, which would entail assessing the disparities in economic network in the absence of LinkedIn. However, we posit that traditional networking mechanisms, such as connections established during college and in the workplace, as well as networking that may be associated with "old boys clubs" attitudes and actions, would likely exhibit even greater disparities for historically marginalized individuals who have faced systemic barriers and discrimination than those created through a platform such as LinkedIn.

Total network size

Figure 1 illustrates the relative average network size categorized by both race and gender (panel 1), as well as by ZIP Code median income (panel 2) Additionally, Figure A.1, included in the Appendix, presents the corresponding trends for

Figure 1

Relative average total network size



gender and race separately, allowing for an examination of the overall disparities in network size. Table A.1 shows the underlying values.

We begin by examining gender gaps in network size. Our findings reveal that men have larger average relative network sizes compared to women for each racial groups investigated. Specifically, the overall average relative size for men is 1.166, indicating that their average network size surpasses the national average by 16.6%. On the other hand, women exhibit an average relative size of 0.822, suggesting that their network size is 17.8% smaller than the national average. These estimates together imply that men's average network size is approximately 41.6% larger than that of women (or, conversely,

women's networks are 29.5% smaller).² Notably, the gender gap is relatively narrower for White members, with White men's networks being approximately 36.9% larger than White women's. In contrast, the widest gender gap is observed among Black members, with Black men's networks being approximately 56.1% larger than Black women's.

We now shift our focus to examining racial disparities in network size. When considering each gender group individually and overall, Asian members exhibit the largest networks, surpassing the Self-ID national average by 17.4%. They are followed by White members, whose networks are marginally larger than the national average by 0.3%, while Black members have

² The percentage difference between groups can be estimated directly from the relative averages. For example, for the gender gap, men have a 41.6% larger average network size than women, as calculated by $1.166/0.822-1=0.416$. Alternatively, women have 29.5% smaller network than men because $0.822/1.166-1=-0.295$.

networks that are 12.7% smaller, and Latino members have the smallest average network sizes, which are 20.0% smaller than the self-ID national average.

Furthermore, our analysis underscores the significance of intersectionality, highlighting the experiences of Black women and Latinas in particular. Black women, on average, have networks that are 28.6% smaller than the Self-ID national average and 38.4% smaller than the average network size of White men. Similarly, Latinas have the smallest average network sizes, 33.5% smaller than the Self-ID national average and 42.6% smaller than the average network size of White men.

We also uncover significant disparities based on the socio-economic status of communities. Specifically, members residing in ZIP Codes categorized in the lowest quartile of median income exhibit an average network size that is 23.9% smaller than the national average, and a striking 41.9% smaller than members living in ZIP Codes in the top quartile of median income. Notably, this disparity surpasses even, for instance, the gap between Latina women (the group with the smallest average network size) and White men. This relationship remains consistent across all four quartiles of ZIP Code median income, indicating that residing in wealthier communities is associated with larger average network sizes. However, as noted earlier, this is likely at least partly due differences between these groups in the composition of members across professions.

Network growth rates

Average over the last year

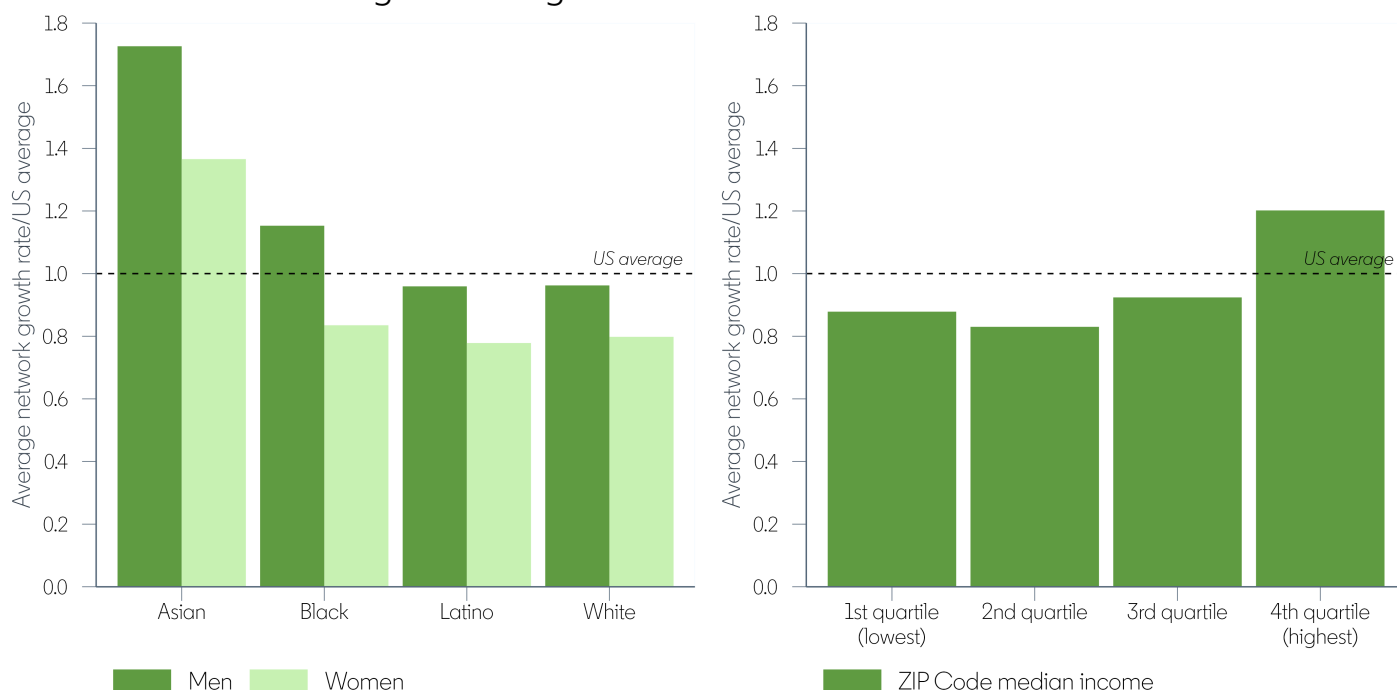
To provide insights into disparities in network growth rates, we next assess the average number of new connections established per month between the one-year period of May 2022 and April 2023. Figure 2 presents these gaps categorized by both race and gender, as well as by ZIP Code median income. Figure A.2 presents the results for gender and race separately. For a more detailed breakdown of the underlying values, please refer to Table A.2.

The overall patterns in network growth rates closely resemble those observed for total network size (Figure 1). Men, Asian and White members, as well as individuals residing in higher income communities, tend to experience faster growth in their networks than the national average. However, there are two notable differences in these results compared to total network size—one for the growth rate of Black members' networks, and one for the comparison across ZIP Code median income. We discuss these below.

When examining gender, men are adding connections at a rate that is 8.4% higher than the national average per month, whereas women are adding connections at a rate that is 11.9% lower than the monthly average. Consequently, this indicates that men are adding connections at a rate that is 23.1% higher than that of women each month. This gender gap holds true across racial groups. Black members exhibit the largest gender gap in network growth rates, with Black men adding connections at a rate that is 38.1% higher than Black women. On the other hand, White members exhibit the smallest gender gap,

Figure 2

Relative average network growth rates



with men adding connections at a rate that is 20.6% higher than that of women.

When analyzing the differences across race and ethnicity in terms of network growth rates, we uncover a notable difference compared to the earlier findings discussed regarding total network size. Specifically, we observe that Black members are adding new connections at a rate that surpasses that of White members by 11.8%, although still 0.9% below the national average.³ This finding indicates that Black members are making progress in catching up with faster network growth, although a divide in network sizes persists. Similar to the previous analysis, Asian members exhibit the highest growth rates, with their networks growing at a rate that is 54.6%

higher than the national average. On the other hand, Latino members have the slowest growth rates, with their networks expanding at a rate that is 13.5% lower than the national average. White members, in comparison, experience network growth rates that are 11.4% below the national average.

Once again, the significance of intersectionality becomes apparent in our analysis. Specifically, we find that Latinas have the slowest rate of adding new connections—22.2% below the national average. While Black members, on average, demonstrate a higher rate of adding new connections compared to White members, it is noteworthy that Black women still fall behind White men in this regard.

³ As a reminder, these differences can be driven by a number of factors, including difference rates at which members participate in different occupations or are represented on the LinkedIn platform.

Furthermore, we observe that individuals residing in higher income ZIP codes tend to experience faster-growing networks. However, the disparity is primarily noticeable between individuals in the top quartile of ZIP codes compared to those in the remaining quartiles. That is, members living in the first, second, and third quartile ZIP Codes of median income have relatively similar network growth rates to each other, in contrast to total network size differences shown in Figure 1. Members living in ZIP codes within the highest quartile of median income added connections at a rate that was 20.2% higher than the national average per month. In contrast, the bottom three quartiles, encompassing individuals residing in ZIP codes with median incomes below the 75th percentile, exhibited relative averages in the range of 85-95. This indicates that their monthly connection growth rates were 5 to 15% lower than the national average.

Trends over time

Building upon the analysis of network growth rate differences, we now shift our focus to examining these trends over time. Figure 3 illustrates these trends, comparing them to the national averages (ratio = 1). In the past five years, Asian men and women have exhibited an upward trajectory, with their network growth rates increasing. Conversely, Black, Latino, and White men have been losing ground in relation to the national average, which has been influenced by the significant growth rates of Asian networks. Meanwhile, Black, Latina, and White women have consistently remained approximately 20% below the national average, maintaining a relatively steady position throughout the examined period with only slight increases.

Figure 3

Relative average new connections each month



Figure A.3 provides a deeper examination of the trends by estimating the relative gaps compared to the network growth rate of White men. This approach allows us to better observe changes in the gaps over time. The figure reveals that most of the gaps have been narrowing in comparison to White men's network growth rate. Additionally, Figure A.3 presents the race and gender gaps separately, offering a clearer view of the significant progress women have made relative to men over the years. Five years ago, men were adding new connections at a rate approximately 45% higher than that of women. However, the gap has since decreased and now stands at less than 25% higher. This highlights the substantial gains made by women in closing the gender gap in network growth rates.

Figure 3 also includes the trends in network growth rates based on ZIP Code median income. The lowest two quartiles consistently exhibit the smallest growth rates, followed by the 3rd quartile, with the 4th quartile (representing the highest income group) showing the largest growth rate. Similarly, Appendix Figure A.3 presents these trends in terms of gaps relative to the highest income quartile. In contrast to the significant narrowing observed for gender and some race patterns, we do not observe the same level of substantial gap reduction over time for ZIP Code median income. Nevertheless, there is evidence of some narrowing of the gaps across all quartiles after the peak in 2020 for the gaps in network growth rates based on ZIP Code median income.

Decomposing network growth rate gaps

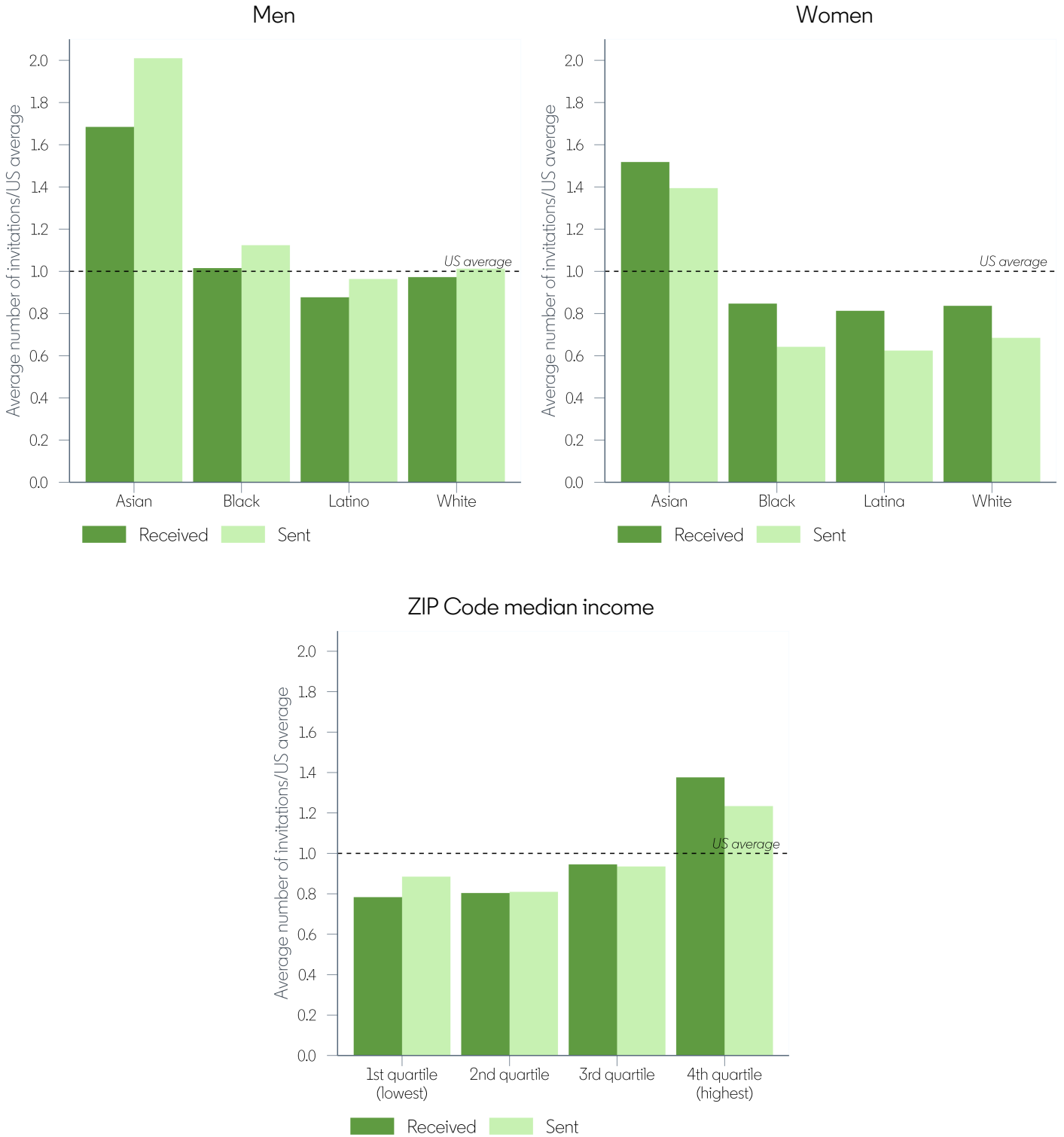
Women, underrepresented racial groups, and members residing in lower income ZIP Codes consistently exhibit smaller networks. Additionally, many of these groups experience slower network growth rates, although there are indications of some narrowing of the gaps, particularly for women and Black and Latino members. However, an important question arises regarding the factors contributing to these observed differences. To begin addressing this question, we delve into the inputs that contribute to the number of new connections made. This analysis allows us to explore these inputs through the examination of four distinct elements:

$$\text{Num. connections} = \text{Pr(inv. sent accepted)} * \text{Num. inv. sent} + \text{Pr(inv. received accepted)} * \text{Num. inv. received}$$

The total number of new connections can be calculated as the sum of two products. The first product involves multiplying the number of new invitations a member sends by the fraction of invitations that were sent that were subsequently accepted. The product captures the new connections established through invitations initiated by the member. The second product involves the number of new invitations received multiplied by the fraction of received invitations that were accepted by the member. This represents the new connections formed through invitations received by the member. We examine gaps in the number of invitations sent and received, acceptance rates of invitations sent and received, and finally bring all four elements together to explore reasons for the observed gaps.

Figure 4

Relative average new invitations sent and received each month



Invitations

We begin first by focusing on the number of invitations sent and received. Figure 4 illustrates the relative average number of monthly connections sent and received, providing an overview of the trends. For a detailed analysis of the trends by race and gender, Appendix Figure A.4 offers a breakdown, while Appendix Table A.3 presents the specific numerical values. On average, men send 40.0% more connection invitations than women and receive 23.9% more invitations. It is worth noting that although men tend to send and receive more invitations than women, men send a higher number of invitations relative to the national average than they receive, while women tend to receive more invitations than they send (all in comparison to the national average).

We also observe similar patterns when examining invitations sent and received by race, although the gaps are slightly smaller in magnitude compared to the differences found in new connections.

Once again, Asian members exhibit the highest numbers of invitations sent and received, and Latino members have the lowest levels of sending and receiving invitations. Moreover, the significance of intersectionality is evident, as Latinas send 37.6% fewer invitations each month than the national average and receive 18.7% fewer invitations each month than the national average—both representing the lowest numbers among the groups examined. Additionally, Black women also have relatively low levels for both sending and receiving invitations. These findings suggest that part of the reason for differences in network growth rates may be related to platform

activity, and it may also reflect differences in their experience on the platform.

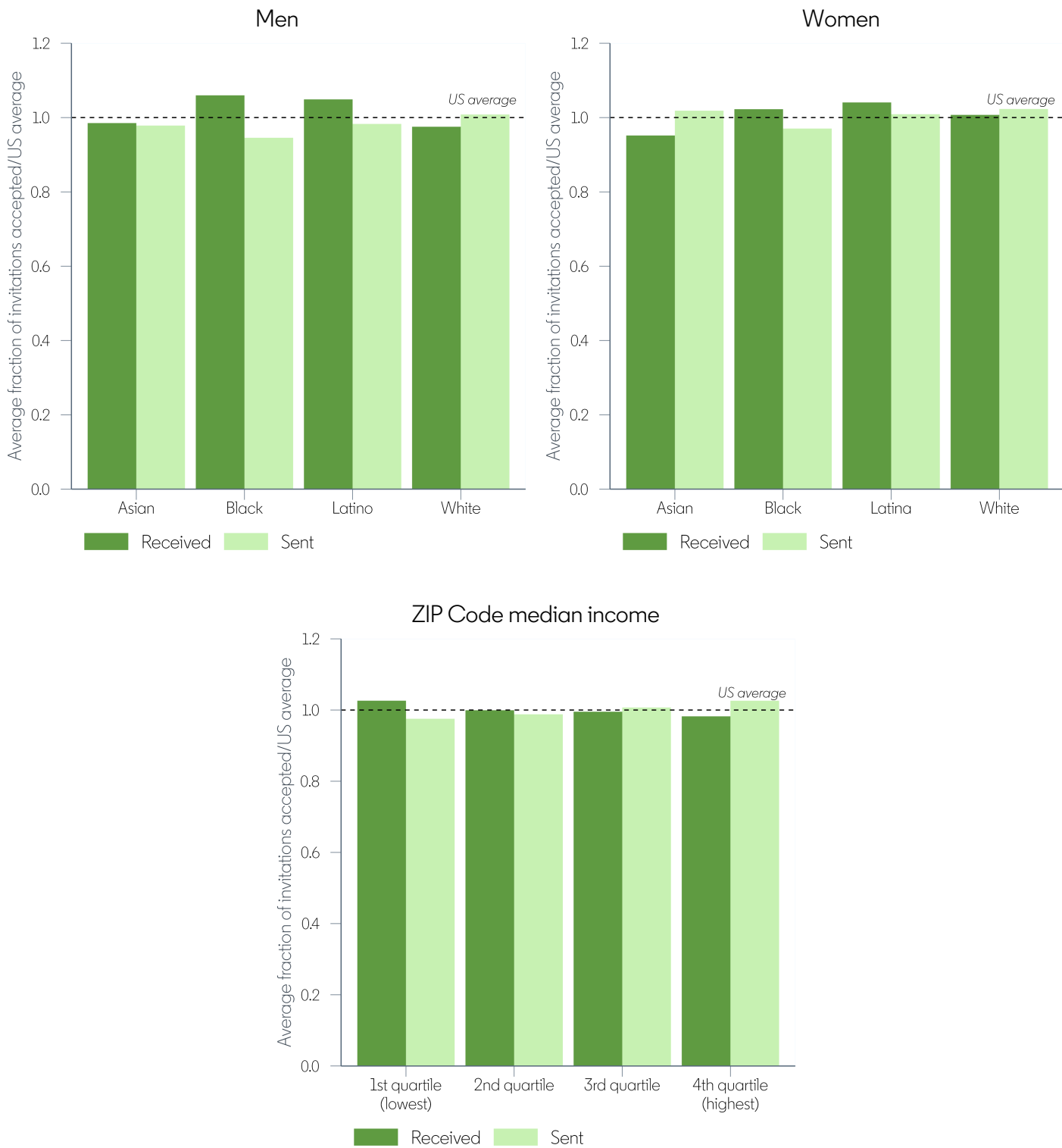
We also observe a significant difference based on ZIP Code median income, particularly between the highest income quartile and the lower quartiles. Interestingly, we find a fascinating reversal of patterns: members living in the highest income quartile receive 16.7% more invitations than they send out each month, whereas members living in the lowest income quartile send 4.9% more invitations than they receive. Put another way, members residing in ZIP Codes with the highest income levels send 39.5% more invitation connections each month compared to those in the lowest income quartile, and receive a far greater number of invitations as well (75.6% more). This finding may serve as a key factor contributing to the observed disparities in network size.

Another way to analyze these trends is by examining the proportion of new connections where the member served as the inviter, rather than the invitee. This ratio is reported in Appendix Table A.3. Interestingly, Black men have the highest ratio, indicating that they are 3.6% more likely than the national average to be the initiator in a newly formed connection. On the other hand, Latinas have the lowest ratio, being 5.3% less likely than the national average to have initiated the invitation.

Additionally, we observe a clear gradient based on ZIP Code median income. Members residing in the lowest quartile of ZIP Code median income are 6.4% more likely than those in the top quartile ZIP Codes to have been the inviter rather than the invitee. This suggests that individuals living in lower income communities are—perhaps out of

Figure 5

Relative acceptance rates of invitations sent and received



necessity—more proactive in initiating connections compared to their counterparts in higher income communities, who can rely on receiving a higher stream of invitations to connect.

Acceptance rates

We next shift our focus to the acceptance rates of invitations sent and received. Figure 5 provides an overview of these results, while Appendix Figure A.5 breaks down the outcomes by race and gender. The gender gap in acceptance rates is relatively small, with men having a slightly higher acceptance rate for invitations received compared to women. However, the acceptance rates for invitations sent by both genders are roughly similar.

In terms of race, we estimate that invitations sent by Black members are accepted at a rate 4.3% below the national average. This disparity is even more pronounced for Black men, with their acceptance rate being 5.4% below the national average—the lowest rate of any of the race and gender groups. Conversely, among men, underrepresented racial groups are more likely to accept invitations compared to White men, with Black men, for example, being 6.0% more likely than the national average to accept invitations.

Similar patterns emerge when considering the local community income. Members residing in the lowest income ZIP Codes have their invitations accepted at a rate 2.5% below the national norm, and 4.9% lower than those living in the highest income ZIP Codes. Detailed results can be found in Table A.4.

Comparisons across inputs to new connections

Analyzing the findings from Figures 4 and 5, it becomes apparent that there are more significant disparities in the counts of invitations sent and received compared to the acceptance rates of those invitations. While both factors contribute to explaining the observed gaps in network growth rates, the invitation counts appear to play a larger role.

Our analysis also reveals that the gaps could potentially be even wider for certain groups. For instance, let's consider the observed gap for Black members. Despite Black members now adding new connections at a faster rate than White members, their larger network growth rates would be even more substantial if it weren't for the lower acceptance rates of invitations from Black members compared to White members. This suggests that while Black members are actively sending and receiving more invitations, the lower acceptance rates hinder the full realization of their network growth potential compared to their White counterparts.

To gain a deeper understanding of the factors influencing network growth rates, we conduct an exercise that involves calculating the predicted network growth rate for each group in two pairs of scenarios. These scenarios aim to isolate the impact of specific factors, assuming that the only differences between groups are attributed to:

Scenario 1: invitation counts versus acceptance rates:

- Case 1: The number of invitations sent and received.
- Case 2: The acceptance rate of invitations sent and received.

Scenario 2: members' own activities versus others' activities:

- Case 1: Members' own activities, encompassing invitations sent and acceptance rates of invitations received.

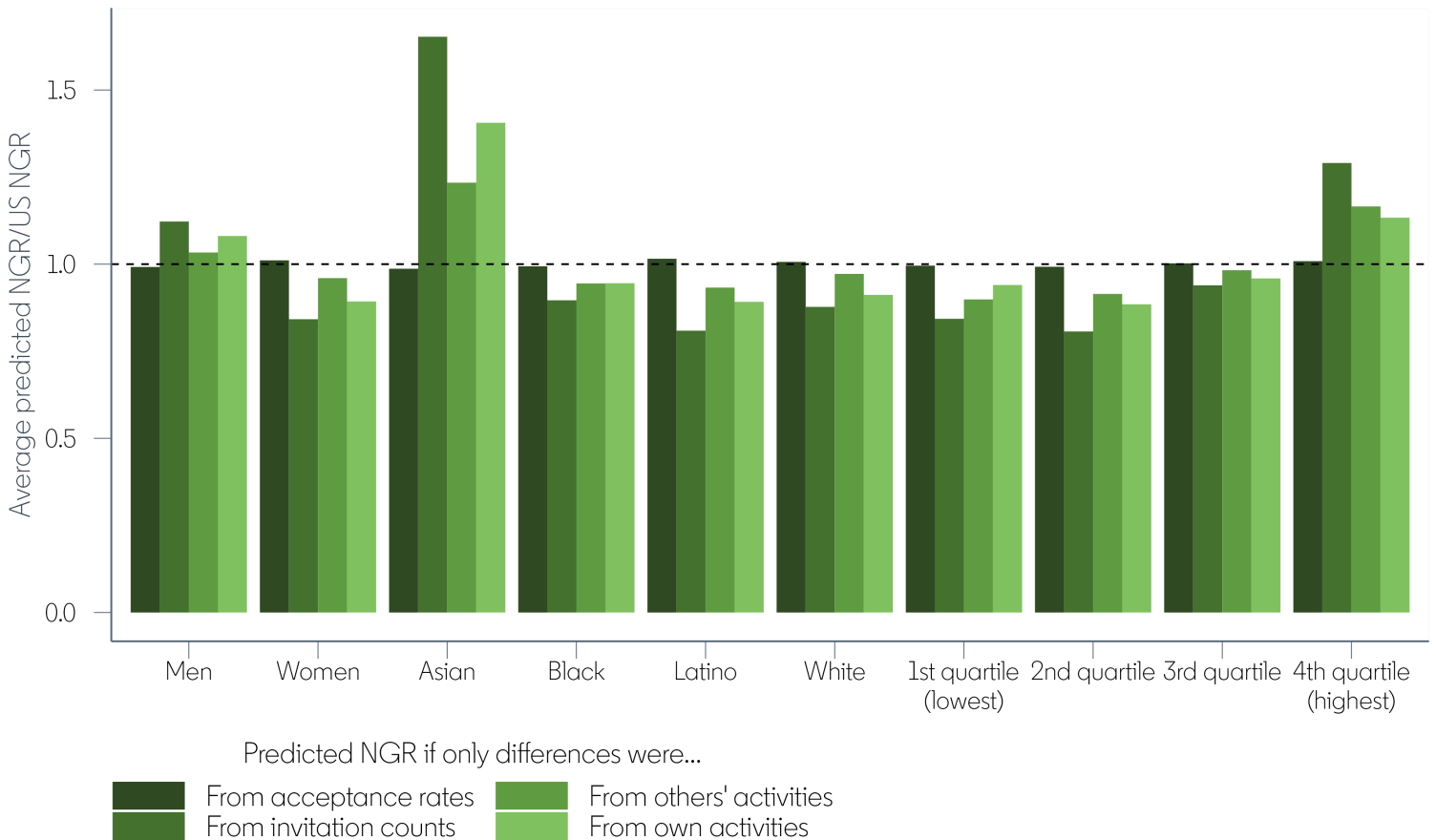
- Case 2: Other members' activities, encompassing invitations received and acceptance rates of invitations sent.

These results are shown in Figure 6. The appendix describes the methodology for estimating these elements.

Beginning with scenario 1, we find that if the observed differences in network growth rates were solely attributable to variations in acceptance rates, with all groups sending and receiving the same number of invitations, then most groups would converge closely to each

Figure 6

Decomposing contributing factors to network growth rates



other and their network growth rate would resemble the national average.

Put another way, the largest disparities, represented by the greatest deviations from the national average (indicated by a value of 1.0), primarily arise from discrepancies in invitation rates. Differences in the frequency of sending and receiving invitations contribute significantly to the observed variations in network growth rates among different groups.

This highlights the importance of members' proactive engagement in initiating connections through invitation activities, as it plays a substantial role in shaping the overall network growth rates and contributing to the observed disparities.

We next examine scenario 2, contrasting the predicted network growth rate due to a member's own activities compared to other members' activities. For gender and race, the gaps tend to be larger from their own activities, although certainly large gaps would remain even if they sent invitations out and accepted invitations received at the national rate. However, for ZIP Code median income, in particular for the lowest income quartile, the gap is driven more by others' activities than by their own activities. This suggests that especially in these cases, but even for the race and gender comparisons, if members from different groups sent invitations and accepted received invitations at the national average rate, significant gaps would still persist in their network growth rates.

Table A4 provides a comprehensive overview of the results discussed, as well as more concrete numbers associated with this exercise. It not only

presents the predicted network growth rates under different scenarios (as shown in Figure 6), but also calculates the proportion of the gap relative to the national norm that can be attributed to case 1 or case 2 in each of the two scenarios.

For instance, if we examine the case of women and men, testing whether differences in invitations sent or acceptance rates are primarily responsible for the observed gaps, we find that women would be 1.1% above the national rate of new connections if the only difference between women and men were their acceptance rates of invitations sent and received. However, when considering the actual differences in invitations sent and received between women and men, assuming both genders had the same acceptance rates as the national average, women would be 15.8% below the national average.

Based on these findings, we estimate that all of the overall gap between women and the national average in network growth rate can be attributed to differences in the rate of invitations sent and received. This underscores the significant impact that variations in invitation rates have on the observed disparities in network growth rates for women.

For most groups in fact, as deduced from Figure 6, more than half of the gap in network growth rate can be attributed to differences in the numbers of invitations—sent and received together—compared to differences in acceptance of invitation rates. The second smallest proportion of the gap arising from differences in invitation rates is observed for Black members, where 94.3% of their gap can be

attributed to differences in invitation rates. The proportion attributable to differences in invitation rates only goes up from there for other groups. This highlights the significant role that invitation rates play in explaining the observed disparities in network growth rates across different groups.

We next return to scenario 2, analyzing the percentage of the gap in network growth rates that can be attributed to the members' own actions versus other members' activities. Among the groups examined, Latino men have the lowest percentage attributable to their own activities, with 3.8% of the observed gap in network growth rate being attributable to the count of invitations they send and the acceptance rate of invitations they receive, as opposed to the number of invitations they receive and the acceptance rate of invitations they send. In other words, the other 96.2% is influenced by the activities of other members. Similarly, individuals living in the 1st quartile of ZIP Code median income have a relatively low percentage, with 37.2% of the observed gap stemming from their own actions.

Interestingly, those in the 4th quartile of ZIP Code median income also have a low percentage attributable to their own actions, but for the gap in the opposite direction—an advantage over the national average. Despite being considerably above the national average in network growth rate, only 44.6% of their advantage can be attributed to their own activities. The remaining 55.4% is driven by their higher rate of receiving invitations and other members' higher acceptance rates of their invitations. This offers a fascinating contrast between the different experiences of members living in the lowest

quartile of income ZIP Codes and those living in the highest quartile of ZIP Code median income.

For several of the other groups, over half of the gap can be attributed to their own activities, even if a large gap still would remain if they were at the national levels for invitations sent and received invitations accepted.

These findings shed light on the varying contributions of individuals' own actions and the actions of others in shaping the observed gaps in network growth rates. It highlights the influence of external factors, such as the behavior of other members, in driving network expansion for several demographic groups experiencing below-average network growth.

Conclusion

This white paper focuses on analyzing the disparities in network size and growth rates based on gender, race, and the income levels of LinkedIn members' communities. Economic networks play a crucial role in facilitating career opportunities, making it essential to understand the gaps that exist in these networks. By decomposing the elements of network growth, we aim to additionally gain insights into the factors contributing to these disparities.

We observe significant gaps in total network size based on gender, race, and ZIP Code median income. White members, men, and individuals residing in high-income ZIP Codes tend to have larger networks compared to Black and Latino members, women, and those living in lower income communities. These disparities highlight the unequal distribution of network resources among different demographic groups.

However, although many of the disparities in network size persist in network growth rates, there are some exceptions and positive developments worth noting. First, Black members currently experience faster-growing networks compared to White members, indicating progress in network expansion. Second, while income remains a factor, the difference in growth rates for new connections is not as pronounced as it is for overall network size. Individuals from lower-income backgrounds have opportunities to forge new connections and bridge the gap—by sending more invitations and accepting a higher rate of invitations sent to them potentially, but also through local networking and mentoring activities. But the onus is not only on individuals from lower-income backgrounds. People in the top income quartile and with larger networks would also benefit greatly from diversifying their connections and ensuring that they encompass individuals of different gender, race/ethnicity, and socio-economic lines.

Furthermore, when analyzing the change over time, we observe a favorable trend of narrowing disparities in network growth rates. This is particularly evident in the significant reductions we measured in the gender gap in the times series over the past five years, as well as gap reductions for many of the race and ethnicity groups. Unfortunately, we do not see the same narrowing of the network growth rate gap by ZIP Code median income.

Upon examining the factors contributing to network growth, we observe that many of the observed disparities persist across all four inputs: invitations sent, invitations received, acceptance rates of sent invitations, and acceptance rates of received invitations. Notably, the total number of

invitations sent and received emerges as significant drivers of these disparities. We also find that, while some of these differences can be attributed to individual member activity, such as the number of invitations sent and the likelihood of accepting received invitations, much of the gap can be attributed to factors potentially external to the member and beyond their control. These factors include the number of connection invitations they receive and the probability of their sent invitations being accepted. These findings highlight the multifaceted nature of networking disparities and suggest the presence of systemic factors that influence networking opportunities.

For example, Latinos have a 2.0% lower likelihood of invitations they send being accepted compared to White members, and they receive 7.5% fewer invitations than White members. Similarly, members living in the 1st quartile (lowest income) ZIP Codes have a 4.9% lower probability of invitations they send being accepted than members living in the top quartile, and receive 43.0% fewer invitations. Thus, even if women, Latinos, and members living in lower communities had the same rate of sending invitations and accepting invitation requests—actions they can control—they would still have smaller network growth rates than men, White members, and members living in the top quartile of ZIP Code median income. Of course, while race and ethnicity are correlated with community income, there are many Black, Latino, and Asian members who live in the top quartile of ZIP Code median income, and many White members who live in the bottom quartile.

Even where there underrepresented groups have made strong progress in network growth rates, they are still impacted by gaps in the inputs. For

example, Black members—who are currently growing their networks at a faster rate than White members—would have even faster convergence of the still-existent gap in total network size if their invitations sent out were accepted at the same rate as White members. But their invitations are 8.1% less likely to be accepted overall. These findings underscore the presence of systemic challenges that contribute to the observed disparities in network growth rates.

It is important to acknowledge the limitations and caveats of this research. It is crucial to note that the presented results do not establish causal relationships nor necessarily imply bias or discrimination. The observed disparities in network size and growth rates can be influenced by various factors such as how active different groups leverage LinkedIn, differences in their occupations, and industries, their own shared-lived experiences, and other potential variables that may or may not be directly linked to gender, race, and community income. Further analysis is necessary to delve deeper into the role of these factors and determine how controlling for them might contribute to a better understanding of the observed gaps in network size and growth. By conducting more comprehensive research into some of the intersection of these and how gaps are minimized when looking at group differences within occupation, industry and platform activity, we can gain valuable insights into the complex dynamics at play and potentially uncover additional factors that contribute to these disparities.

Additionally, our analysis is limited by the population we observe; this is particularly true for analyses involving race/ethnicity, which rely on

members having voluntarily self-identified their race and ethnicity on LinkedIn.

Despite the presence of observed disparities, there are reasons for optimism. First, we believe that the economic network disparities identified in this study are relatively smaller than what would be, thanks to the existence of platforms like LinkedIn. Without such platforms, individuals would likely rely on traditional networking mechanisms, which could further historically and systematically marginalize groups and disproportionately benefit those who have established networks, connections through prestigious educational institutions, and membership in exclusive clubs with formal networking structures. Second, we have observed a trend of narrowing gaps and, in some cases, even a reversal of disparities. This provides hope for future convergence and suggests that progress is being made for each of these groups. By acknowledging these positive developments, we can strive for continued improvements in creating more equitable and inclusive economic networks.

There are several actions that can be taken to promote greater equity in network growth and size. Some of these actions pertain to the platform itself, which can leverage AI and programmatic encouragement to narrow gaps in areas such as invitations received and acceptance rates of invitations sent. Campaigns can also be organized to encourage members of certain communities to reach out and send invitations to more of their known community, enabling further second-degree introductions and connections. Members can take actions to grow their own networks, purposefully seeking out connections with people who they have met and

who will be helpful in their careers. Formal and informal networking activities and mentoring can also help narrow gaps in network size and growth.

Additionally, communities and government policies can play a role in fostering informal and offline networking opportunities, which would subsequently translate into improvements in online network dynamics and characteristics. By addressing these aspects, we can work towards creating a more inclusive and equitable networking environment.

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Methodology

For all analysis, we limit attention to non-restricted, active accounts. For the race analysis, we additionally limit to individuals who have self-identified their race and gender.

Data and Privacy This body of work represents the world seen through LinkedIn data, drawn from the anonymized and aggregated profile information of LinkedIn's 930+ million members around the world. As such, it is influenced by how members choose to use the platform, which can vary based on professional, social, and regional culture, as well as overall site availability and accessibility.

In publishing these insights from LinkedIn's Economic Graph, we want to provide accurate statistics while ensuring our members' privacy. As a result, all data show aggregated information for the corresponding period following strict data quality thresholds that prevent disclosing any information about specific individuals.

Gender Classification Gender identity isn't binary, and we recognize that some LinkedIn members identify beyond the traditional gender constructs of "man" and "woman." If not explicitly self-identified, we have inferred the gender of members included in this analysis either by the pronouns used on their LinkedIn profiles or inferred on the basis of first name. Members whose gender could not be inferred as either man or woman were excluded from this analysis.

Decomposition of inputs into NGR Let π_j^S be the probability for a member in group j of having an invitation they sent (S) accepted, and π_j^R the acceptance rate of invitations received. Further, let I_j^S be the number of invitations a member in group j sends, and I_j^R the number of invitations received. Then, we may estimate the contribution of each element as follows, where NGR_j is the total network growth rate of members in group j .

$$NGR_j = \pi_j^S I_j^S + \pi_j^R I_j^R$$

A special value of this is the national level, given by

$$NGR_{US} = \pi_{US}^S I_{US}^S + \pi_{US}^R I_{US}^R$$

We can next calculate what the network growth rate would be for a given group holding constant certain elements. For example, consider if we wanted to estimate the NGR for group j only considering differences due to varying levels of invitations they receive. In that case, we want to hold constant π_j^S and π_j^R and only vary I_{US}^S and I_{US}^R . This could be estimated by

$$E[NGR_j | \pi_{US}^S, \pi_{US}^R] = \pi_{US}^S I_j^S + \pi_{US}^R I_j^R$$

We could then divide this by NGR_{US} to get an estimate of the relative NGR (compared to the national average) for group j only considering differences due to how their invitations received and sent differ from the national averages of the same.

From this we calculate four key estimates of NGR, and the resulting relative gap from the national average:

- Relative gaps due to differences in invitation rates: $rg_{invitations} = \frac{\pi_{US}^S I_j^S + \pi_{US}^R I_j^R}{NGR_{US}}$
- Relative gaps due to differences in acceptance rates: $rg_{accepts} = \frac{\pi_j^S I_{US}^S + \pi_j^R I_{US}^R}{NGR_{US}}$
- Relative gaps due to their own activities: $rg_{own} = \frac{\pi_{US}^S I_j^S + \pi_j^R I_{US}^R}{NGR_{US}}$
- Relative gaps due to others' activities: $rg_{other} = \frac{\pi_j^S I_{US}^S + \pi_{US}^R I_j^R}{NGR_{US}}$

Next, consider a case when there are gaps. Note that

$$\begin{aligned} (rg_{accepts} - 1) + (rg_{invites} - 1) &= \frac{\pi_{US}^S I_j^S + \pi_{US}^R I_j^R}{NGR_{US}} - 1 + \frac{\pi_j^S I_{US}^S + \pi_j^R I_{US}^R}{NGR_{US}} - 1 = \\ &= \frac{1}{NGR_{US}} (\pi_{US}^S I_j^S + \pi_{US}^R I_j^R + \pi_j^S I_{US}^S + \pi_j^R I_{US}^R - 2\pi_{US}^R I_{US}^R - 2\pi_{US}^S I_{US}^S) \\ &= \frac{NGR_j}{NGR_{US}} - 1 + \frac{1}{NGR_{US}} (\pi_{US}^S - \pi_j^S)(I_j^S - I_{US}^S) + \frac{1}{NGR_{US}} (\pi_{US}^R - \pi_j^R)(I_j^R - I_{US}^R) \\ &\approx \frac{NGR_j}{NGR_{US}} - 1 \end{aligned}$$

The last equality holds only approximately, due to the product of small gaps being approximately equal to zero (in practice, the correlation coefficient between this sum and the directly-estimated $\frac{NGR_j}{NGR_{US}} - 1$ across all of the groups is 0.9997). This is useful because

this means that $\frac{r_{\text{accept rates}}-1}{NGR_{j-1}}$ provides an estimate of the proportion of the relative gap attributable to differences in acceptance rates, and $\frac{r_{\text{invites}}-1}{NGR_{j-1}}$ is an estimate of the proportion of the relative gap attributable to differences in invitation rates. A similar exercise can decompose the gap for own activities versus others' activities.

Appendix

Table A.1

Relative average total network size

Dimension	Group	Relative average size
Gender*	Men	1.166
Gender*	Women	0.822
Race†	Asian	1.174
Race†	Black	0.873
Race†	Latino	0.800
Race†	White	1.003
Race X Gender†	Asian Men	1.389
Race X Gender†	Asian Women	1.007
Race X Gender†	Black Men	1.115
Race X Gender†	Black Women	0.714
Race X Gender†	Latino Men	0.952
Race X Gender†	Latina Women	0.665
Race X Gender†	White Men	1.158
Race X Gender†	White Women	0.846
ZIP Code median income*	1st quartile(lowest)	0.761
ZIP Code median income*	2nd quartile	0.812
ZIP Code median income*	3rd quartile	0.962
ZIP Code median income*	4th quartile(highest)	1.310

†Relative to Self-ID national average, *Relative to full national average

Table A.2

Relative average network growth rate

Dimension	Group	Relative average size
Gender*	Men	1.084
Gender*	Women	0.881
Race†	Asian	1.546
Race†	Black	0.991
Race†	Latino	0.865
Race†	White	0.886
Race X Gender†	Asian Men	1.726
Race X Gender†	Asian Women	1.366
Race X Gender†	Black Men	1.153
Race X Gender†	Black Women	0.835
Race X Gender†	Latino Men	0.959
Race X Gender†	Latina Women	0.778
Race X Gender†	White Men	0.962
Race X Gender†	White Women	0.798
ZIP Code median income*	1st quartile(lowest)	0.879
ZIP Code median income*	2nd quartile	0.830
ZIP Code median income*	3rd quartile	0.924
ZIP Code median income*	4th quartile(highest)	1.202

†Relative to Self-ID national average, *Relative to full national average

Table A.3

Invitations sent and received rate

Dimension	Group	Invitations sent	Invitations received	Fraction of new connections as inviter
Gender*	Men	1.142	1.093	1.000
Gender*	Women	0.816	0.882	0.997
Race†	Asian	1.695	1.590	0.988
Race†	Black	0.877	0.926	1.005
Race†	Latino	0.789	0.840	0.979
Race†	White	0.857	0.907	0.999
Race X Gender†	Asian Men	2.010	1.684	1.006
Race X Gender†	Asian Women	1.394	1.518	0.971
Race X Gender†	Black Men	1.124	1.015	1.035
Race X Gender†	Black Women	0.642	0.847	0.978
Race X Gender†	Latino Men	0.963	0.877	1.010
Race X Gender†	Latina Women	0.624	0.813	0.947
Race X Gender†	White Men	1.012	0.972	1.005
Race X Gender†	White Women	0.685	0.836	0.992
ZIP Code median income*	1st quartile(lowest)	0.883	0.783	0.976
ZIP Code median income*	2nd quartile	0.809	0.804	0.958
ZIP Code median income*	3rd quartile	0.935	0.946	0.938
ZIP Code median income*	4th quartile(highest)	1.234	1.376	0.918

†Relative to Self-ID national average, *Relative to full national average

Table A.4

Relative acceptance rates for invitations sent and received rate

Dimension	Group	For invitations sent	For invitations received
Gender*	Men	0.994	0.988
Gender*	Women	1.012	1.010
Race†	Asian	0.996	0.973
Race†	Black	0.957	1.048
Race†	Latino	0.995	1.046
Race†	White	1.015	0.993
Race X Gender†	Asian Men	0.978	0.985
Race X Gender†	Asian Women	1.018	0.952
Race X Gender†	Black Men	0.946	1.060
Race X Gender†	Black Women	0.970	1.022
Race X Gender†	Latino Men	0.983	1.049
Race X Gender†	Latina Women	1.009	1.041
Race X Gender†	White Men	1.008	0.975
Race X Gender†	White Women	1.023	1.007
ZIP Code median income*	1st quartile(lowest)	0.975	1.026
ZIP Code median income*	2nd quartile	0.988	0.999
ZIP Code median income*	3rd quartile	1.007	0.995
ZIP Code median income*	4th quartile(highest)	1.026	0.982

†Relative to Self-ID national average, *Relative to full national average

Table A.4

Decomposing gaps in new connections

	From acceptance rates	From invitations	Fraction from invitations	From others' activities	From own activities	Fraction from own activities
Men	0.992	1.122	1 [†]	1.033	1.081	0.707
Women	1.011	0.842	1 [†]	0.960	0.893	0.728
Asian	0.987	1.653	1 [†]	1.234	1.406	0.634
Black	0.994	0.896	0.943	0.945	0.945	0.498
Latino	1.015	0.809	1 [†]	0.933	0.892	0.617
White	1.006	0.877	1 [†]	0.972	0.912	0.759
Asian Men	0.981	1.880	1 [†]	1.261	1.600	0.697
Asian Women	0.992	1.444	1 [†]	1.218	1.217	0.499
Black Men	0.991	1.080	1 [†]	0.973	1.098	1 [†]
Black Women	0.991	0.724	0.969	0.921	0.794	0.722
Latino Men	1.009	0.929	1 [†]	0.940	0.998	0.038
Latina Women	1.022	0.700	1 [†]	0.930	0.791	0.750
White Men	0.995	0.996	0.424	0.994	0.998	0.289
White Women	1.017	0.745	1 [†]	0.948	0.814	0.783
1st quartile (lowest)	0.996	0.843	0.973	0.899	0.940	0.372
2nd quartile	0.993	0.807	0.963	0.915	0.885	0.574
3rd quartile	1.002	0.939	1 [†]	0.983	0.959	0.701
4th quartile (highest)	1.009	1.290	0.971	1.166	1.133	0.446

[†] Values at zero or one result from cases when one input leads to NGR above the national average while the other input leads to NGR below the national average. In such cases, it is set equal to the input which dominates in the calculation (i.e., yielding a fraction above one would be set to one, and below zero would be set to zero).

Figure A.1

Relative average network size, gender and race

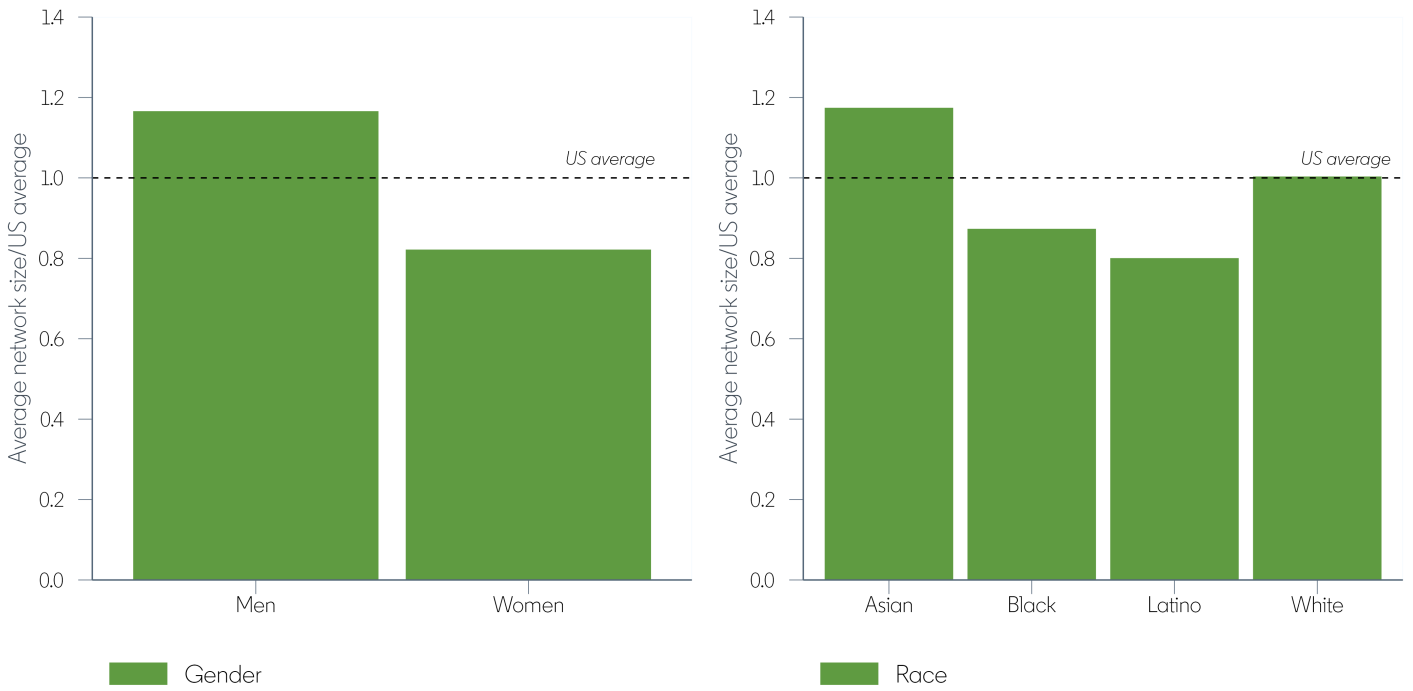


Figure A.2

Relative network growth rate, gender and race

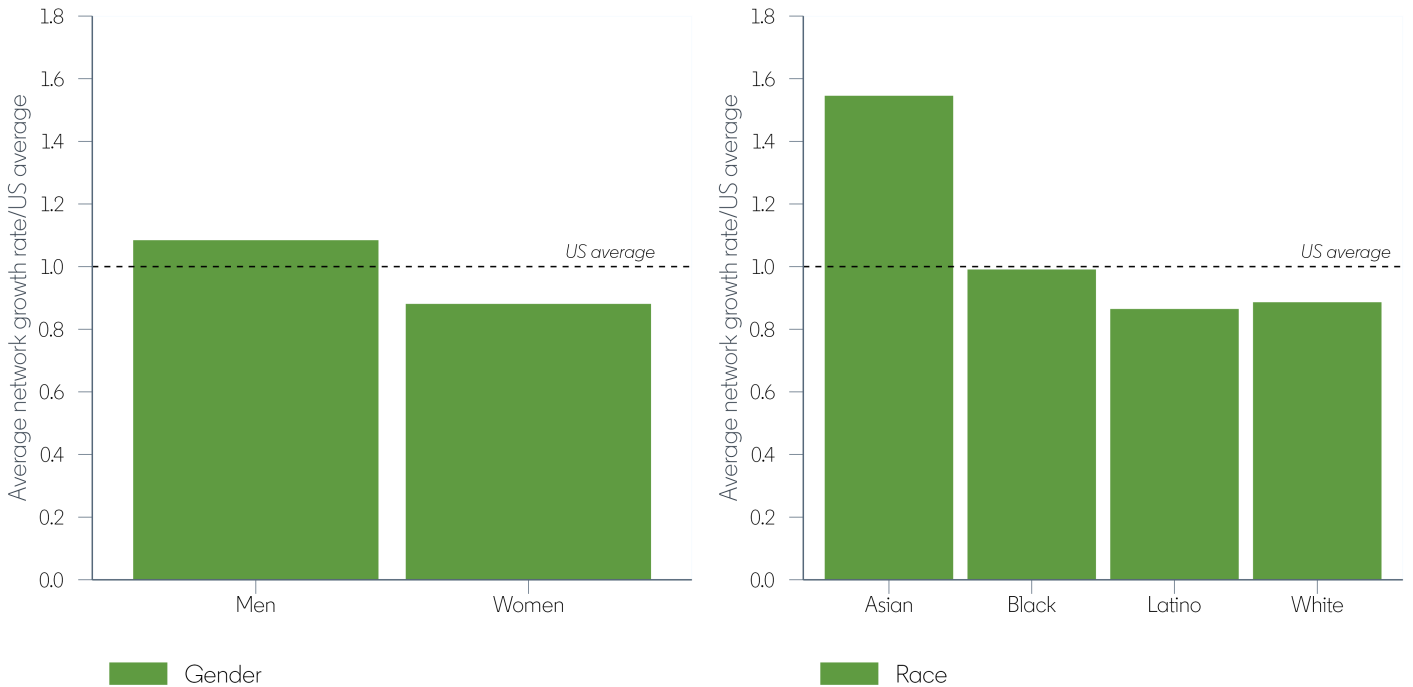


Figure A.3

Gaps in relative average network growth, gender by race and ZIP Code median income



Figure A.4

Relative average new invitations sent and received each month, gender and race

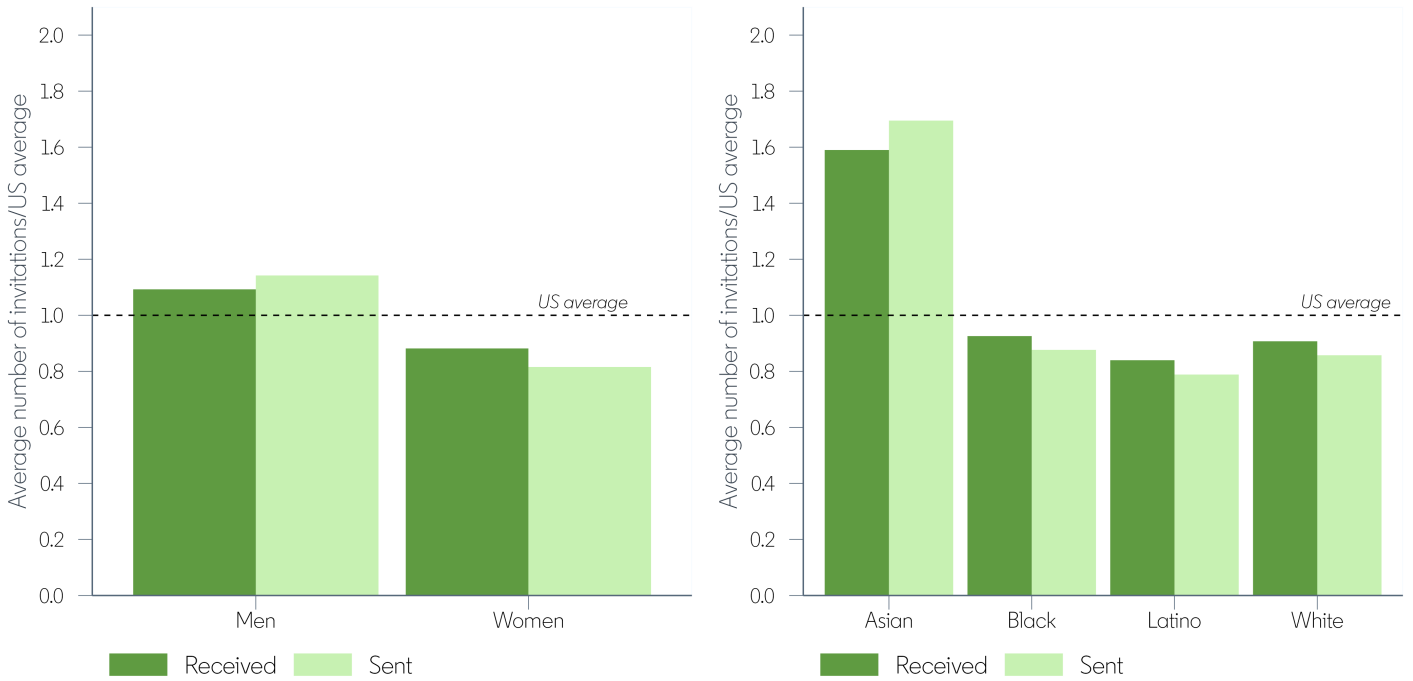


Figure A.5

Relative acceptance rates of new invitations sent and received each month, gender and race

